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Heart Sound Analysis for Diagnosis of Heart Diseases in Newborns

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Abstract

Many studies have been conducted in recent years to automatically differentiate normal heart sounds from heart sounds with pathological murmurs using audio signal processing in early stage. Serious cardiac pathology may exist without symptoms. The purpose of this study is developing an automatic heart sound signal analysis system, able to support the physician in the diagnosing of heart murmurs at early stage of life. Heart murmurs are the first signs of heart disease. We screened newborns for normal (innocent) and pathological murmurs. This paper presents an analysis and comparisons of spectrograms after smoothing phonocardiogram signals (PCG) with Cepstrum, Bispectrum, and Wigner Bispectrum techniques. A comparison between these methods has shown that higher order spectra, as Bispectrum and Wigner bispectrum, gave the best results.

Keywords: Heart murmurs, Spectral, Cepstrum, Bispectrum, Wigner Bispectrum

1. Introduction

Despite remarkable advances in imaging technologies for heart diagnosis, clinical evaluation of cardiac defects by auscultation is still a main diagnostic method for discovering heart disease. In experienced hands, this method is effective, reliable, and cheap. Beside, tools for objective analysis and adequate documentation

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of the findings are not effective yet.

Heart murmurs are often the first sign of pathological changes of heart valves, and they are usually found during auscultation in primary health care. Heart murmurs are an important feature to identify cardiac disorders in childhood, infancy, and especially in newborns. Unrecognized heart disease in newborns carries a serious risk of avoidable mortality, morbidity and handicap [1]. The main advantages for early recognizing a cardiac disease are that newborns will be seen and assessed earlier and in better clinical conditions.

Cardiac murmurs occur frequently in healthy children, but it can also be a feature associated to many forms of congenital heart disease, including regurgitation, stenosis of heart valves, left to right shunt lesions at the atrial, ventricular, or great arterial levels. Careful examination reveals innocent systolic murmurs in about 72% of school-age children. A high prevalence of innocent murmur also has been documented in infant and neonates. Seven types of innocent heart murmurs are reported in children, i.e. still's murmur [2], innocent pulmonary flow murmur, innocent pulmonary branch murmur of infancy, supraclavicular bruit, venous hum, mammary souffle, and cardiorespiratory murmur. Generally, clinical history and physical examination are diagnostic for these murmurs.

When a physician visits a newborn with phonocardiography (PCG), heart murmurs are the most common abnormal auscultation finding. When a murmur is detected, the physician must decide whether to classify it as pathological or innocent.

Although an innocent heart murmur does not represent current or future illness, often a physician who suspects that a newborn is healthy still orders an echocardiogram for reassurance, although the cost of an echocardiogram is not negligible. The result of this practice is a misallocation of healthcare funds (i.e. false positive) While it is clearly important to avoid type-I errors when healthy newborn are sent for echocardiogram, it is also important to avoid type-II errors (i.e. False negative), which occur when a newborn who has a pathological heart murmur is sent home without proper treatment [3].

Many studies have been performed with the goal of providing tools for practical murmur detection and improving the diagnostic accuracy of physicians in small practice settings. In particular, Ahlstrom et al. [1] investigated issue of feature extraction for systolic heart murmur classification. For more information on the problem of diagnosing systolic heart murmurs (See, for instance, McGee [4]). Heart sounds have been recorded from newborns in other research activities focused on adult, children or infants [5, 6]. Different methods are used for feature extraction of heart murmurs, the most important being spectral analysis [7, 8]. In this paper, we discuss some speech and audio processing techniques for analyzing heart sounds. In order to achieve a high-resolution result for heart murmurs analysis we used high order spectral methods, such as Bispectrum and Wigner bispectrum.

2. Methods

2.1. Pre-processing

The recording of PCG usually has a sampling frequency higher than 8000Hz. In the event that the recording environment is not well controlled; noise is coupled to the PCG. To avoid unpredictable effects brought by noise, filtering out the unwanted noise becomes important for later processing. That is the reason why the first step of signal processing consists of filtering heart sounds, since the main spectrum of first heart sound (S1) and second heart sound (S2) stay within the range of 200Hz, the system that has been implemented filters the original heart sound using a band-pass filter Butterworth, with 3rd order and cut-off frequencies set at 50Hz and 200Hz. An electronic stethoscope has been used to record heart sounds, giving rise to a dataset at 44k Hz and converted to 4k Hz. The second step of pre-processing uses a segmentation algorithm, aimed at identifying the heart sound components S1 and S2 (see Figure. 1).

Typically, heart sounds consist of two regularly repeated thuds, known as S1 and S2 and appearing one after the other for every heartbeat. The time interval between S1 and S2 is the systole, while the gap between S2 and the next S1 corresponds to the diastole. Currently, the detection is performed manually; however, we are planning to identify of S1 and S2 with an automatic procedure in the next future. The segmentation method is based on the timing between those high amplitude components. The fact that the time for systole is always less than the time for diastole is the basis for this process.

The largest section of systolic and diastolic murmur, common to all database samples, was chosen for analysis (represented with 400 and 700 points, for systolic and diastolic murmurs respectively).

The main characteristics of heart sounds, such as their timing relationships and components, frequency contents, their occurrence in the cardiac cycle, and the envelope shape of murmurs can be quantified by means of advanced digital signal processing techniques.

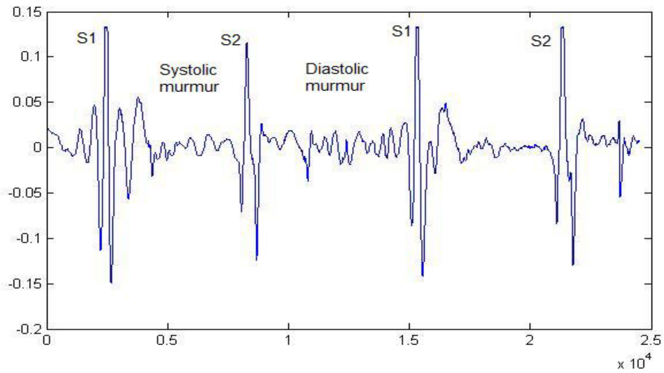

Fig. 1. Sample of two cycle heart sound, where components S1 and S2 are highlighted

2.2. Smoothed Nonparametric Spectral Estimation via Cepstrum Thresholding

Cepstrum thresholding is shown to be an effective way for obtaining a smoothed nonparametric estimate of the spectrum of an audio signal, such as heart sound. Introducing the cepstrum thresholding-based spectral estimator for non-stationary signal is of interest to researchers in spectral analysis and allied topics, such as audio signal processing.

The cepstrum of $\{y(t)\}$ can be defined as follows:

$$c_k = \frac{1}{N}\sum_{l=0}^{N-1} \ln(\phi_l)\, e^{i\omega_l k}. \tag{1}$$

K=0, 1,…, N-1.

Let us consider a stationary, real valued signal $\{y(t)\}_{t=0}^{t=N-1}$ its periodogram estimate $\hat{\phi}_p$ for $p = 0,1,\ldots,\frac{N}{2}$ is given by:

$$\hat{\phi}_p(\omega) = \frac{1}{N}\left|\sum_{t=0}^{N-1} y(t) e^{-j2\pi ft}\right|^2. \tag{2}$$

where it is assumed that $\varphi_p > 0, \forall p$. The cepstral coefficients have several interesting features, one of which is mirror symmetry, defined as:

$$c_{N-k} = c_k \qquad k = 0,1,\ldots,\frac{N}{2}. \tag{3}$$

In other words, only half of the sequence, $c_0,...,c_{(N/2)-1}$ is distinct and the other half is obtained from via (3). In $c_1,...,c_{(N/2)-1}$, using the periodogram estimate in (2), a common estimate of the cepstral coefficients is obtained by replacing $\phi(\omega)$ in $\hat{\phi}_P(\omega)$ in (5), which gives [9].

$$\hat{c}_k = \frac{1}{N}\sum_{l=0}^{N-1}\ln\left[\hat{\phi}_p(\omega_l)\right]e^{j\omega_l k} + \gamma\delta_{k,0} \qquad k = 0,\dots,\frac{N}{2}. \tag{4}$$

where $\delta_{k,0} = \begin{cases} 1 & if\ k=1 \\ 0 & otherwise \end{cases}$ and $\gamma = 0.577216$ (the Euler's constant).

It can be shown (see, e.g. [9]) that with large samples the estimated cepstral coefficients $\{\hat{c}_k\}_{k=0}^{N/2}$ are independent normally distributed random variables. In symbols $\hat{c}_k \sim N(C_K, S_K^2)$ with:

$$s_k^2 = \begin{cases} \dfrac{\pi^2}{3N} & if\ k = 0, \dfrac{N}{2} \\ \dfrac{\pi^2}{6N} & if\ k = 1,\dots,\dfrac{N}{2}-1 \end{cases}. \tag{5}$$

Keeping in mind the above equations, the idea behind cepstrum thresholding is straightforward. Let $\hat{c}_k$ be a new estimate of $\hat{c}_k$ with $\hat{c}_k = 0$ and mean squared error (MSE) equal to c_k^2 .This estimate is preferred to as $\hat{c}_k$ long $c_k^2 \le s_k^2$ as. Now let

$$S = \left\{k \in \left[0, \frac{N}{2}\right] \middle| c_k^2 \le s_k^2\right\}. \tag{6}$$

And let $\widetilde{S}$ be an estimate of S . Thresholding $\{\hat{c}_k\}_{k\in\widetilde{S}}$ gives the following new estimate of c_k :

$$\widetilde{c}_k = \begin{cases} 0 & if\ k \in \widetilde{S} \\ \hat{c}_k & otherwise \end{cases} \qquad k = 0,\dots,\frac{N}{2}. \tag{7}$$

A good estimate of *S* is given by (see [10] for details):

$$\widetilde{S} = \left\{k \in \left[0, \frac{N}{2}\right] \middle| |\hat{c}_k| \le \mu s_k\right\}. \tag{8}$$

Where the parameter μ controls the risk of concluding that $|c_k|$ is "significant" while this is not true, the so called "false alarm probability". The following values of μ are recommended in [9, 11] for $N \in (128, 2048)$ and $\mu = \mu_0 + \frac{N-128}{1920}$.

For sample lengths $N < 500$, which are most commonly encountered in applications, we recommend $\mu_0 = 2$ *and* 4 for narrowband and broadband signals respectively, whereas for $N \ge 500$ we suggest $\mu_0 = 3$ *and* 5 for narrowband and broadband signals respectively.

This implies that μ will belong to the interval. $(\mu_0, \mu+1)$ for other intervals of the sample length, *N*. Similar rules can be given. The smoothed spectral estimate corresponding to $\{\hat{c}_k\}$ is given by:

$$\hat{\phi}_{cep}(\omega_l) = \exp\left[\sum_{k=0}^{N-1}\hat{c}_k e^{-j\omega_l k}\right] \qquad l = 0,\dots,N-1. \tag{9}$$

where the subscript *cep* signifies its cepstrum dependence. The final scaled spectrum estimate $\hat{\phi}_{cep}(\omega_l)$ is then given by $\hat{\phi}_{cep}(\omega_l) = \hat{\alpha}\widetilde{\phi}_{cep}(\omega_l) \qquad l = 0,\dots,N-1.$

The proposed nonparametric spectral estimate is obtained by a simple scaling

$$\hat{\alpha} = \frac{\sum_{l=0}^{N-1} \hat{\phi}_P(\omega_l)\tilde{\phi}_{cep}(\omega_l)}{\sum_{l=0}^{N-1} \tilde{\phi}_{cep}^2(\omega_l)} \quad (10)$$

2.3. Bispectrum

The third-order spectrum, called bispectrum, is a particular example of higher-order spectrum, defined as the Fourier transform of third-order cumulants sequence. The power spectrum is member of the class of higher-order spectra. For the sake of completeness, let us recall that second order statistics such as autocorrelation and power spectrum provide important information in analysis of Gaussian, stationary and linear processes.

m_x=E(x). *(11)*

m^2_x(i)=E{X(n) . X (n+i)}. *(12)*

Higher order statistics, used in the analysis of Gaussian, stationary and non-linear processes, typically allow to obtained important results. Higher order statistics are calculated upon higher order moments (HOM) such as m^3 and m^4 , i.e., third and fourth order moment, defined as follows:

m^3_x (i, j)= E{X(n).X(n+i).X(n+j)}. *(13)*

m^4_x (i, j,k)= E{X (n).X(n+i).X (n+j).X (i, j, k)}. *(14)*

It is worth noting that moments give more accurate results in the analysis of deterministic signals, while cumulants give more accurate results in the analysis of random signals [12]. Power spectrum of random signals is defined in terms of DFT, i.e., discrete Fourier transform (see Equation 5).

$$B^x = (f_1, f_2) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} C_3^x(m,n) e^{-j2\pi(mf_1+nf_2)}. \quad (15)$$

In the event that the signal is a stationary random process with real values, we can write:

$$B(w_1, w_2) = X(w_1) \cdot X(w_2) \cdot X^*(w_1, w_2). \quad (16)$$

As bispectrum analysis is not easy to calculate, this slice of spectrum obtained from a bispectrum is used for giving an idea in the analysis of data that do not exhibit nonlinear or Gaussian distribution in the signal.

2.4. Wigner Bispectrum

Wigner high-order spectrum is an extension of Wigner-Ville distribution; it keeps the advantages of Wigner–Ville distribution and has also the advantages of High-Order Spectra. The High-Order Spectra has been used widely in the non-gauss and non-stationary realm, which is quite applicable to PCG signals. by combining Wigner- Ville distribution we could get the time-frequency characters at the same time. The study has improved that under the low SNR circumstances the Wigner Bispectrum (WHOS in the third-order moment domain) is better than Wigner-Ville distribution [13].

The High-Order Spectra of Wigner-Ville Distribution of signal x (t) is defined as follows [14]:

$$W(t, f_1, f_2, \dots f_k) = \int_{-\infty}^{+\infty} \dots \int_{-\infty}^{+\infty} x^*\left(t - \frac{1}{k+1}\sum_{m=1}^{k}\tau_m\right) \times \prod_{i=1}^{k} x\left(t + \frac{k}{k+1}\tau_i - \frac{1}{k+1}\sum_{j=1, j\neq 1}^{k}\tau_j\right)\exp(-j2\pi f_i \tau_i) d\tau_i . \quad (17)$$

$W(t, f_1, f_2, \dots f_k)$ represents the order k Fourier transform of a k-dimensional local function. Let us define R_{kt} as follows: $R_{kt} = x(t-\alpha)\prod_{i=1}^{k} x(t+\tau_i-\alpha)$where α is delay of time now W_{kx} can be defined as:

$$W_{kx}(t, f_1, f_2 \dots f_k) = R_k(\tau_1, \tau_2 \dots \tau_k)\prod_{i=1}^{k}\exp(-j2\pi f_i \tau_i)\, d\tau \quad (18)$$

Finally, the definition of Wigner Bispectrum is given as follows:

$$W_{2x}(t, f_1, f_2.) = \int_{\tau_1}\int_{\tau_2} x^*\left(t - \frac{1}{3}(\tau_1 + \tau_2)\right) x\left(t + \frac{1}{3}(2\tau_1 - \tau_2)\right)\exp(-j2\pi(f_1\tau_1 + f_2\tau_2))\, d\tau_1 d\tau_2 \quad (19)$$

3. Results and Discussion

This section reports experimental results and discusses the applications of each of the smoothed nonparametric spectral estimation via cepstrum thresholding, bispectrum and Wigner bispectrum to the analysis and diagnosis of heart murmur.

Smoothed nonparametric spectral estimation via cepstrum thresholding is shown in Figure 2.

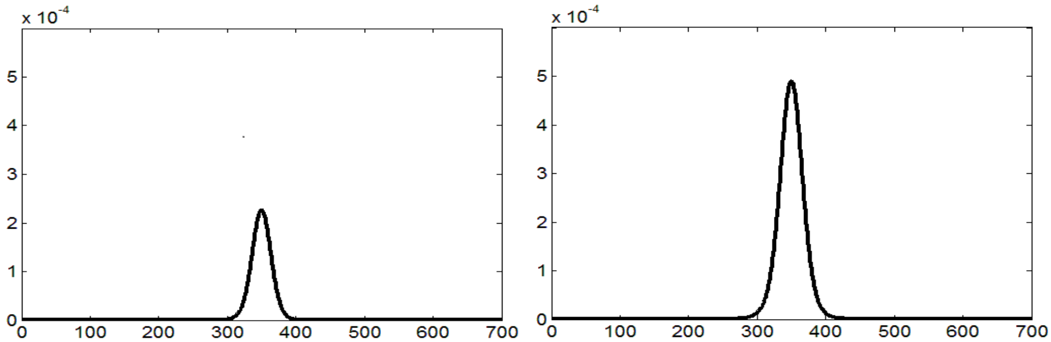

Fig. 2. Smoothed nonparametric spectral estimation with cepstrum thresholding (a) innocent (b) pathological murmurs

The above figures depict the results related to spectrum estimate via cepstrum thresholding, whereas the one reported below illustrate the result. Amplitude changes are observed.

Figure 3 shows the bispectrum for a normal (Figure 3a) and a pathological (Figure 3b) heart murmur. Figure 3a clearly highlights the existence of significant peaks in the bispectra.

Thorough experimental results shows that the same kind of heart murmurs have significant similarities in their bispectra shapes and in the locations of peaks.

Figure 4 shows the Wigner bispectrum for normal and pathological heart sounds. A careful analysis of Figure 4 allows to identify the first (S1) and second (S2) cardiac sound. It clearly contains two heart murmurs. It gives a strong support in the task of separating innocent and pathological murmurs.

The result validated by measurement with a standard echocardiography device of 58 samples and features are validated by cross-validation performance.

4. Conclusions

We demonstrated that audio signal processing and a suitable data encoding have significant potential as an accurate diagnostic tool for discriminating heart sound data as innocent and pathological murmurs in newborns. The analysis of heart sounds provides information that can be very useful for a physician when deciding whether or not to release a newborn or to send him/her for an echocardiogram. This technology is for high-volume screening of newborns for heart disease. The software system proposed in this work can be considered a first release of this diagnostic tool.

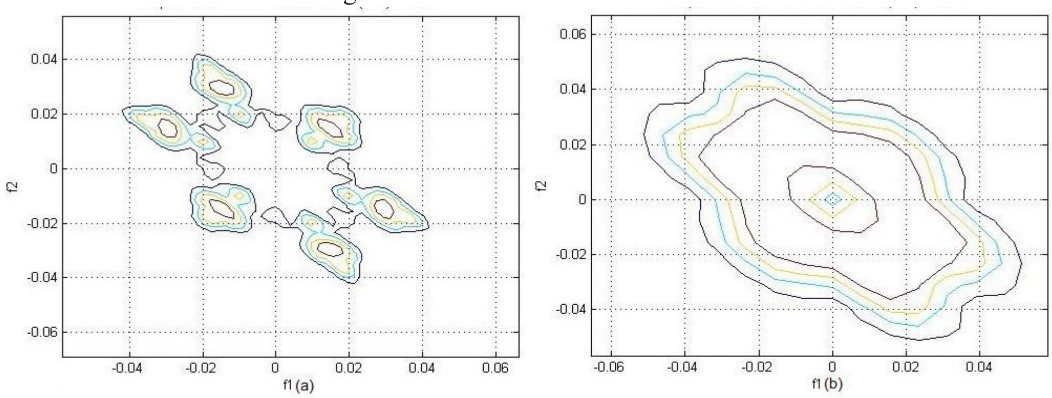

Fig. 3. Contour plot of bispectrum for (a) normal and (b) pathological murmurs.

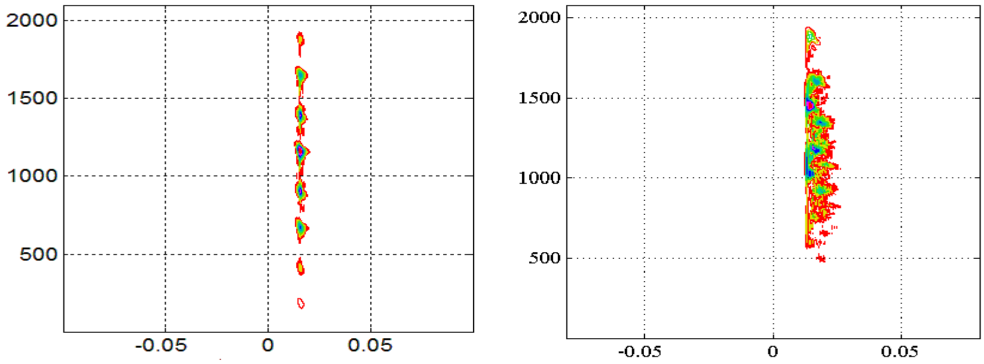

Fig. 4. Wigner bispectrum of: (a) heart sound with innocent murmur and (b) heart sound with pathological murmur.

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